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Design of an Intelligent Lotus Root Node Cutting Machine Control System Based on PLC and Machine Vision1

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Abstract

Aiming at the problems of traditional lotus root processing, such as reliance on manual labor, low efficiency, and poor accuracy in node cutting, this paper designs an intelligent lotus root node cutting machine control system based on PLC and machine vision. The system integrates three modules: motion control, vision inspection, and human-machine interaction. With Siemens S7-200 SMART PLC as the control core, it handles logic decision-making and motion control. The Jetson Nano embedded platform equipped with the YOLOv5s object detection algorithm is used to identify and locate lotus root nodes in real time, and the position information is transmitted to the PLC via Socket communication. Based on this, the PLC drives the stepper motor to precisely control the cutting tool to complete node removal. Meanwhile, the system is equipped with a human-machine interface based on a Weinview touch screen, enabling status monitoring, parameter setting, and multi-level permission management. Experimental results show that the system achieves a node recognition accuracy of 92% and a processing speed of 6 nodes per minute. It features low cost, easy implementation, and stable operation, providing an effective intelligent solution for lotus root deep processing in small and medium-sized enterprises.

Keywords

Lotus Root Node Cutting; PLC; Machine Vision; YOLOv5; Control System.

1. Research Background

Lotus root is an important aquatic vegetable in China, widely cultivated. Improving the deep processing industry chain of lotus root is of great significance for increasing the added value of agricultural products and promoting farmers' income. Lotus root node cutting is a key step in the fresh-cut processing of lotus root, directly affecting product appearance and subsequent processing efficiency. However, the irregular shape and crisp texture of lotus root make traditional manual cutting inefficient, inaccurate, and pose safety hazards. Xiao Zhengqiang and Huang Yong [1] pointed out, through a systematic analysis of patents related to lotus root processing machinery, that the lotus root processing industry is at a critical stage of transitioning from manual to mechanized automation, and there is an urgent market demand for low-cost, high-efficiency intelligent equipment. Therefore, developing a low-cost, easy-to-maintain intelligent lotus root node cutting device has significant practical implications.

Regarding the development of fresh-cut processing equipment, Nie Huzi et al. [2] studied the current status and bottlenecks of fresh-cut processing equipment in China, indicating that automation and intelligence are the future directions, requiring the integration of vision inspection and programmable control technology to improve processing accuracy. Guo Lei et al. [3] studied an improved YOLOv5 method for small object detection, significantly enhancing recognition accuracy for small targets by optimizing the feature extraction network, providing technical support for detecting lotus root nodes, which are locally indistinct features. Han Ping et al. [4] proposed a lightweight recognition method for various vegetables based on improved YOLOv5n.

In the field of intelligent processing of root vegetables, Liang Xin [5] studied a machine vision-based intelligent variable slicing control system for potatoes, designing a linkage scheme between vision inspection and servo control, verifying the feasibility of combining vision technology and motion control. Cao Tianzhi [6] explored the application of computer vision and deep learning in defect detection and automatic grading of yams, further proving the broad applicability of vision inspection technology in the processing of root agricultural products. Additionally, Qi Xuepeng and Ren Jiming [7] designed a monitoring system for PLC and industrial robots, demonstrating the information interaction and control integration capabilities of PLC in complex automation equipment, providing a reference for human-machine collaboration and remote monitoring.

In summary, although existing studies have explored the application of machine vision and PLC in agricultural product processing, a systematic design specifically for lotus root node cutting is still lacking. This study aims to integrate PLC control technology, machine vision technology, and human-machine interaction technology to design an intelligent lotus root node cutting machine control system, enabling automatic recognition and precise cutting of lotus root nodes, meeting the urgent demand of domestic enterprises for low-cost, high-efficiency, and easy-to-maintain automation equipment.

2. Overall System Scheme

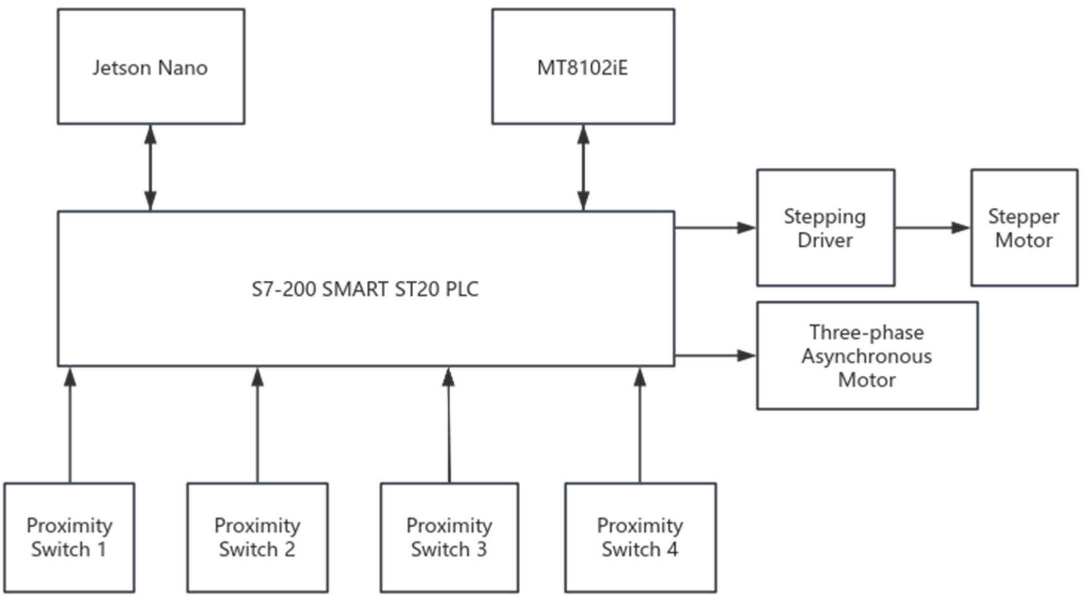

Figure 1. System Structure Block Diagram

The control system adopts a modular design concept. The system structure block diagram is shown in Figure 1. The system takes the PLC as the control core and mainly consists of three modules: vision inspection, motion control, and human-machine interaction.

The vision inspection module is based on Jetson Nano and an industrial camera, using the YOLOv5s model to perform real-time detection of lotus roots on the conveyor belt, obtaining the position information of the nodes. The motion control part uses the S7-200 SMART PLC as the core, receives the position data transmitted by the vision module, and drives the stepper motor to control the movement of the cutting tool. Meanwhile, the PLC receives input signals from proximity switches, buttons, etc., and controls actuators such as the conveyor motor and the cutting tool motor. The human-machine interaction function is realized through a Weinview touch screen, which communicates with the PLC. It can display the system status (such as speed, position, alarm information) in real time and support operation parameter setting and manual control.

3. System Software Design and Implementation

3.1. Software Design of the Vision Inspection Module

The experiment was run on a hardware platform with Intel (R) Core (TM) i7-13650H CPU, 8.00 GB RAM, and NVIDIA GeForce RTX 3050 GPU. The environment was implemented with Pytorch 2.4.1 and CUDA 11.1. The pre-training model weights were obtained by training on the large-scale COCO dataset. The SGD optimizer was used to optimize the overall objective, with a batch size of 16, a learning rate of 0.01, and 100 iterations. The image size used for the model was 640px × 640px.

Lotus root images were collected, and the Make Sense tool was used to annotate lotus root nodes (distinguishing different regions), constructing a dataset containing 2100 images. The dataset was divided into training set, validation set, and test set in a ratio of 7:2:1.

To verify the superiority of the selected algorithm, comparative experiments were conducted on three mainstream object detection models—YOLOv5, YOLOv3, and Faster-RCNN—under the same dataset and training configuration. The main evaluation metrics included mean average precision (mAP@0.5), precision, and model size (storage occupation). The comparison results are shown in Table 1.

Table 1. Comparison of different models

Model	mAP@0.5	Precision	Model size/MB
YOLOv5s (Model 1)	0.8611	0.8482	40.40
YOLOv3 (Model 2)	0.8456	0.8153	324.92
Faster-RCNN (Model 3)	0.8380	0.8069	315.05

From the data in Table 1, it can be seen that YOLOv5 achieved the highest mean average precision (86.11%) and precision (84.82%) among the three models, while its model size was only 40.40 MB, far smaller than YOLOv3 (324.92 MB) and Faster-RCNN (315.05 MB). Although YOLOv3 and Faster-RCNN also have certain detection capabilities, their models are too bulky to be deployed on embedded platforms with limited computing resources (such as Jetson Nano), and real-time performance would be affected. Considering detection accuracy, resource occupation, and deployment feasibility, this study finally chose the lightweight YOLOv5s model as the core algorithm for the vision inspection module of the intelligent lotus root node cutting machine.

Ubuntu 18.04 system was burned onto the Jetson Nano, and the CUDA, OpenCV, and PyCharm development environments were configured. After training the initial weight model, the weight file for detection was copied to the Jetson Nano, and a Python Socket server program was

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written to convert the detected node coordinate information into six-digit BCD code (the first three digits for the left cutting tool, the last three digits for the right cutting tool) and send it to the PLC via Ethernet.

3.2. Software Design of the Motion Control Module

A Socket client program was written on the PLC side to receive the lotus root node position data sent by the Jetson Nano. The received six-digit string was decoded, split, and the data type was converted (BCD code to floating-point number) to serve as the target position for the stepper motor.

The motion control wizard in the STEP 7-MicroWIN SMART software was used to configure parameters such as the pulse equivalent, speed, and acceleration of the stepper motor. Ladder logic was written to call instructions such as AXIS0_CTRL (enable), AXIS0_GOTO (absolute positioning), and AXIS0_RSEEK (return to origin) to achieve precise positioning and reciprocating motion control of the cutting tool. The system control flow is:

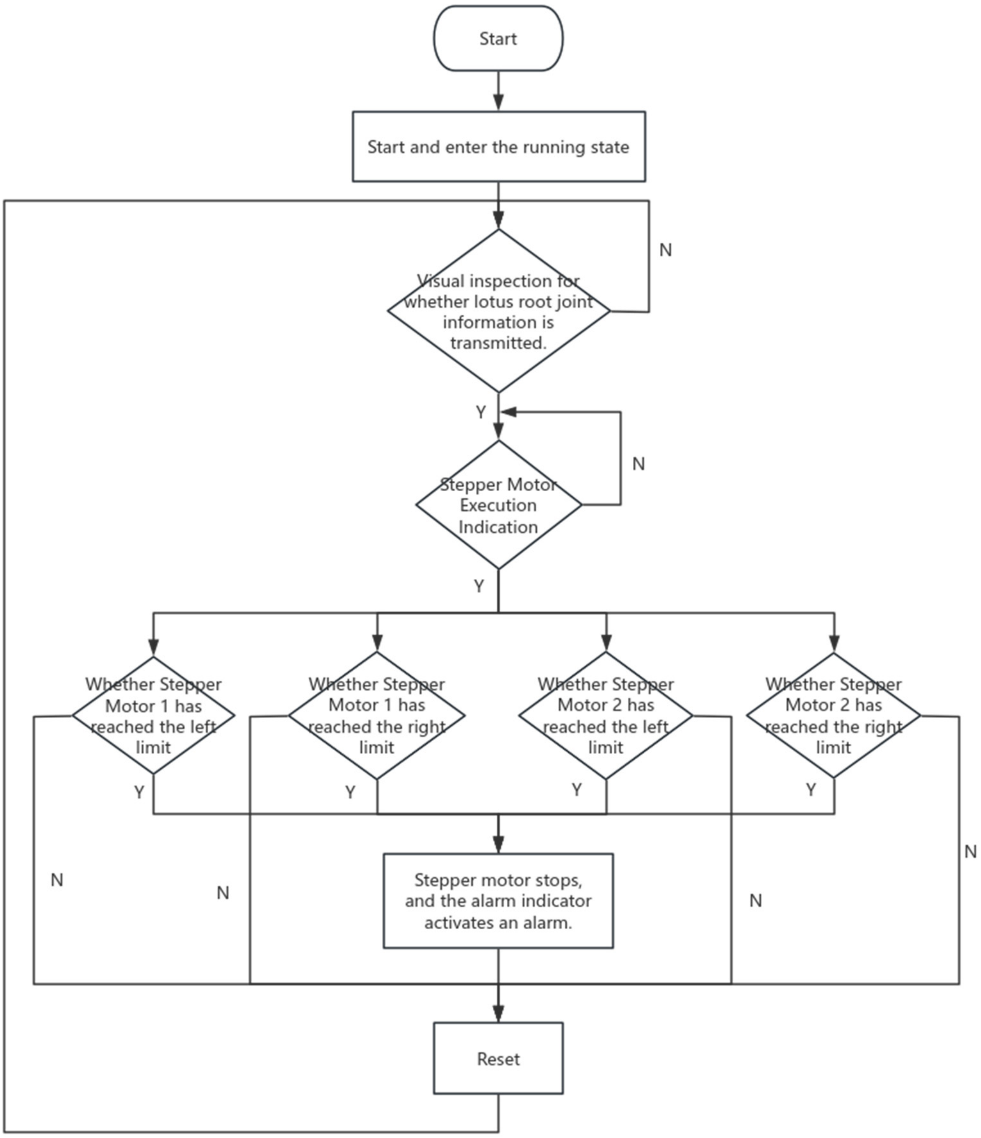

Figure 2. PLC Control Flow Chart

3.3. Design of the Human-Machine Interaction Module

The touch screen interface was designed using EasyBuilder Pro software, and communication with the PLC was established via an RS485 interface (PPI protocol). A monitoring interface was

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set up to display in real time the current speed/position of the stepper motor, the number of cut nodes, the status of left and right limit sensors, etc. An operation interface was provided with system start, stop, and reset buttons, as well as motor jog control in manual mode. An alarm interface was designed to record and display alarm events such as overtravel and login failures. Finally, a user login authority was set: multi-level user permissions were configured to ensure operational safety.

4. System Debugging and Result Analysis

4.1. Individual Module Debugging

For the vision inspection part, the trained YOLOv5s weight file (best.pt) was exported in the PC training environment. After model pre-training, the YOLOv5s model achieved a node recognition accuracy of 92% on the validation set. Running on the Jetson Nano, the detection speed met real-time requirements. A Python main program was written on the Jetson Nano to implement camera reading, model inference, coordinate parsing, and Socket sending. Each frame was scaled to 640×640 and fed into the YOLOv5s model for detection. The center coordinates of the node bounding boxes were extracted, and based on preset red (horizontal) and black (vertical) lines, the system determined whether the current node belonged to the left or right cutting tool area, and calculated the distance the tool needed to move (in mm). Through Ethernet debugging, Socket data transmission between the Jetson Nano and the PLC was successfully achieved.

For the motion control part, the stepper motor jog and return-to-origin functions were first manually tested to confirm that the limit switches were effective. Then, by simulating position data input through the PLC program, it was verified that the motor could accurately move to the specified position, with positioning accuracy meeting the design requirement of ±1 mm.

For the human-machine interaction part, the data exchange between the touch screen and the PLC was mainly tested. All buttons, indicators, and numerical displays functioned normally, and switching between manual and automatic modes was smooth.

4.2. Overall System Integration and Results

After completing the individual module debugging, overall system integration was performed. After power-on, lotus roots were placed on the conveyor belt. The vision inspection module captured images in real time and recognized the nodes. When a node entered the cutting area, the Python program running on the Jetson Nano converted the distance values for the left and right sides into integers from 0 to 999, represented each with 3-digit BCD code, and combined them into a 6-digit string. For example, if the left side needed to move 12 mm and the right side 8 mm, the resulting string would be "012008".

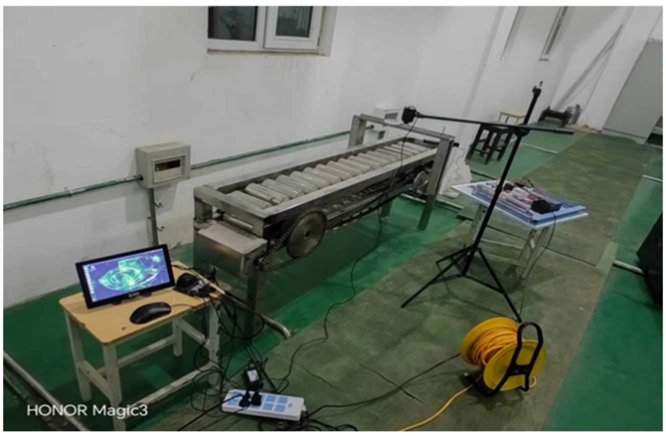

Figure 3. Physical Connection Diagram

A TCP Socket server was created, bound to the IP address of the Jetson Nano (e.g., 192.168.2.1) and a port (e.g., 6666), waiting for the PLC to connect as a client. Once the connection was established, each time a valid node was detected, the 6-digit string was sent.

The Jetson Nano sent the position information to the PLC, and the PLC then drove the stepper motor to move the cutting tool to the specified position for cutting. The whole process realized fully automatic closed-loop control.

The integration results showed that the control system could stably and reliably complete the automatic recognition and cutting of lotus root nodes, achieving a processing speed of 6 nodes per minute, meeting the expected technical specifications.

5. Conclusion

This paper successfully designed and implemented an intelligent lotus root node cutting machine control system based on PLC and machine vision. The system achieves precise recognition and localization of lotus root nodes using the YOLOv5s algorithm, high-precision motion control using PLC and stepper motors, and is supplemented by a user-friendly human-machine interface, effectively solving the problems of low efficiency and poor accuracy in traditional lotus root node cutting. Debugging results show that the system operates stably, with high recognition accuracy and processing efficiency that meets practical requirements. It also features low cost and easy implementation. The results of this study provide a feasible technical solution for the intelligent processing of lotus root and other root vegetables, with good application prospects and promotion value. Future work will focus on optimizing the vision algorithm to cope with more complex working conditions and exploring the application of the system in more agricultural product processing fields.

Acknowledgments

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